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14. ABSTRACT

This is the final report for the period 12/96-12/99. Five projects are described. The first project deals with the role of memory in the deployment of attention in visual search. In laboratory visual search tasks, subjects look for a target item among a variable number of distractor items. It has been generally assumed that rejected distractor items are somehow marked during the course of the search so that attention will not be redeployed to previously rejected items. The reported research shows that any such memory for the course of search is extremely limited. Humans appear to search displays of this sort in an anarchic manner. The second project assessed the speed with which subjects can command the deployment of attention. The results show that commanded search is quite slow (200-300 msec per deployment) compared to the much faster deployments that can be inferred in anarchic search (25-50 msec per deployment)
The third project address a classic problem in visual attention. Are all items processed in parallel or are the processed sequentially, in series. A way to transcend the serial/parallel debate is described. Project Four continues the ongoing development of the Guided Search model of visual search. Specifically, a modification of the computation of bottom-up salienceis described. Finally, project five considers visual search by a moving observer and shows that optic flow stimuli do not have privileged status in human visual search.

15. SUBJECT TERMS

Visual attention, visual search, optic flow, serial and parallel processing, visual memory

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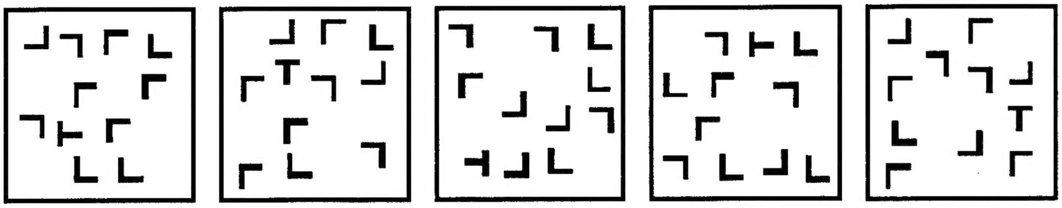
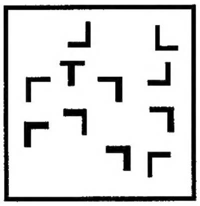
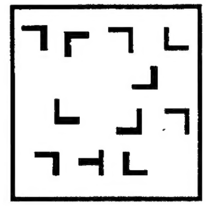
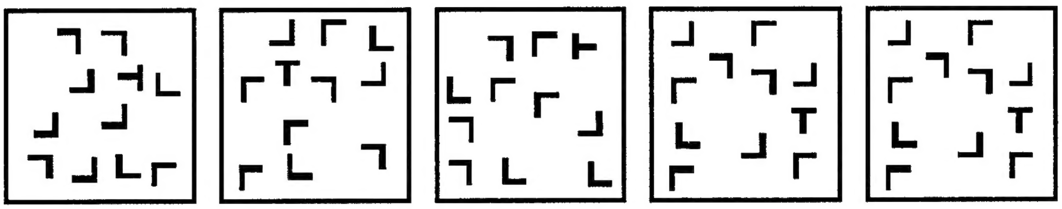


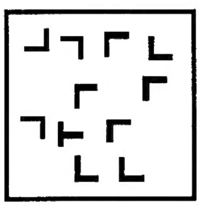


Developing Guided Search 3.0

Final Report for AFOSR award F49620-97-1-0045







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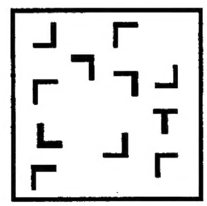
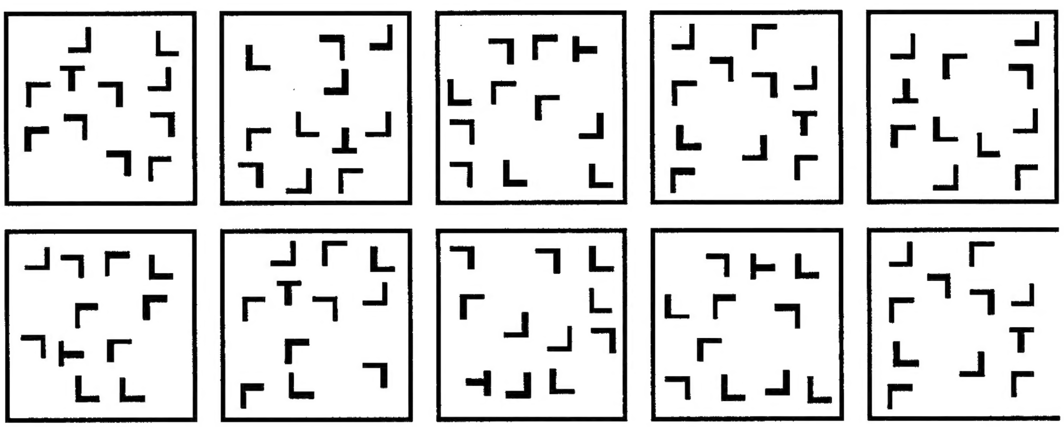
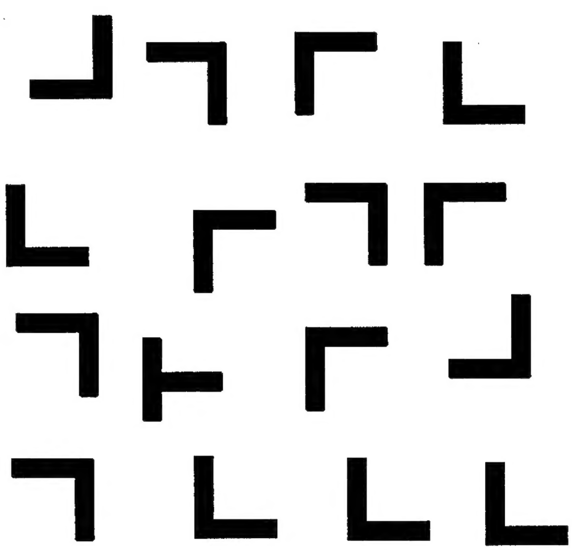




This report provides descriptions of the results of five projects that were conducted with AFOSR support during the period from December, 1996 to December 1999 under award F49620-97-1-0045.

PROJECT 1. The role of memory in the deployment of attention in visual search

In visual search tasks, observers look for a target item among a number of distractor items. Real world examples include searching for a face in the crowd or a tank in a field. For some search tasks, the target cannot be identified (or, perhaps, even seen) until it is foveated. Finding a particular word on a page of text would be an example. In other tasks, while the items are clearly visible, the target is not identified until it becomes the object of attention. As an example, consider Figure One. All 16 items are quite clearly visible.



However, you only identify the target "T" when you attend to it.

How do you perform such a task? Common sense suggests that you deploy attention from item to item until you locate the target. Common sense might also suggest that you should mark each rejected "L" distractor in a manner that would prevent you from revisiting an item that is clearly not the target. Hence, one of the standard models of this sort of visual search has been a

"serial, self-terminating search (Treisman and Gelade 1980). This is shown in cartoon version in Figure 2. If search is serial and self-terminating, then the time required to find a target (reaction time, "RT") will increase linearly with the number of items (the set size). When the target is present, the observer will need to search through half of the items on an average trial before attention is deployed to the target. If no target is present, then all distractor items will need to be attended and rejected before search is ended. As a consequence, the slope of the function relating RT to set size will be twice as steep for target-absent searches as it is for target present (Sternberg 1969). In a search like the one shown in Figure Two, RT increases at a rate of 20-30 msec/item for target-present trials and 40-60 msec/item for target-absent trials (Wolfe 1998).

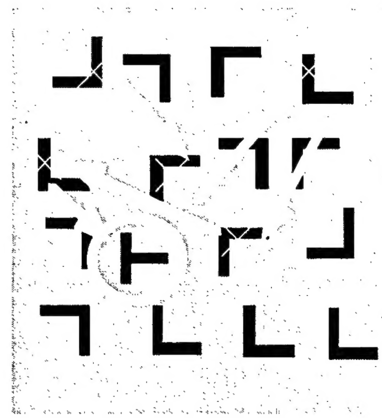


Fig. 2
Serial, self-terminating search

Serial models are not the only models for search. It is also possible to imagine that all items are being processed in parallel and that the observer responds when enough target information accumulates to permit identification of a target or when all items are identified as distractors (Kinchla 1974; Ratcliff 1978; Palmer 1995).

One attribute, shared by standard serial and parallel models of search, is accumulation of information during the course of a search trial. In serial models, that accumulation takes the form of a memory for the location of rejected distractor items (Fig 2). In parallel

models, it is the steady accumulation of information about item identity. We have conducted three lines of experiments seeking to document this memory in visual search. In each case, our results indicate that there is no memory (or, at best, very little). These lines of research will be briefly described below followed by a discussion of the implications of this finding.

Project 1.1 - Dynamic Search

In the most intuitively straight-forward paradigm, the search display was repeatedly and randomly scrambled during the course of the search trial. This is shown schematically for the T among L task in Figure 3:

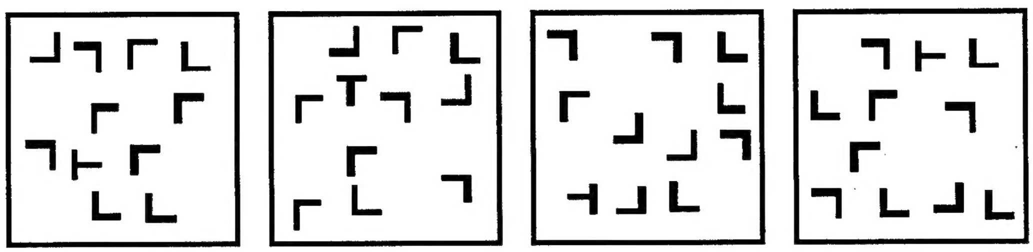


Fig. 3 The dynamic search paradigm

On each frame, all of the items in the display were randomly replotted to new locations. If there was a target present, it was present in all frames but its location changed from frame to frame. Such a method of presentation obviously thwarts the serial marking of rejected distractors. It would also disable many forms of parallel accumulation of information (e.g. any model that proposed location-specific accumulation of information). For serial models, the predicted outcome of this manipulation is clear. If the mean RTs in a standard Static search task produce a slope of X msec/item, slope from Dynamic search should increase to 2X msec/item.

We have run many different versions of this Dynamic search experiment, using different search tasks and varying frame rates (2-10 Hz). We consistently find that the slope in the Dynamic condition is the same as the slope in the Static condition. An example is shown in Figure Four. These are data from a version in which the display was changed every 500 msec. Items could be replotted either to the same locations on each frame or to different locations on each frame. It is clear from the graph (and substantiated by statistical analysis) that the slopes in the Dynamic search conditions do not differ from the Static search slope and that they do differ from the 2X prediction of the standard model.

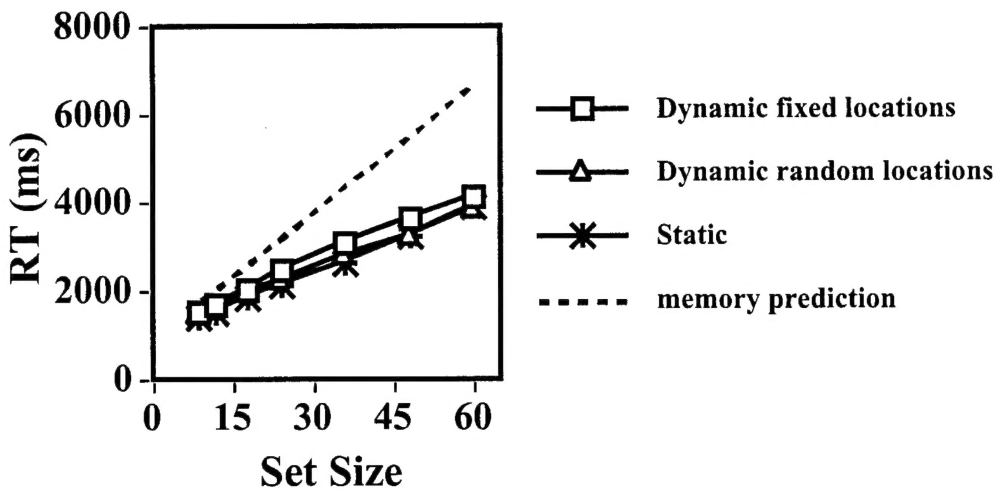


Figure 4: Results of one Dynamic vs Static search experiment

Since it made no difference to the efficiency of visual search when memory was thwarted in the Dynamic search conditions, we suggested that memory for rejected distractors might not be a factor in standard, Static search either. Rather than sampling the display *without replacement* as would seem most reasonable, the data indicate that observers

sample the display *with replacement*, picking a new object of attention without regard for prior history of attentional deployment on that trial. Further details can be found in the Nature paper that accompanies this report (Horowitz and Wolfe 1998).

Project 1.2 Multiple Target Search

In an effort to obtain converging evidence on the presence or absence of memory for rejected distractors, a second task was developed. A sample is illustrated in Figure 5. In this task, observers were asked if there were *at least* N digits in a display of letters. The example shown here could be drawn from a block in which observers were asked if at least four digits were present. This would be a "yes" trial for that task. Another block, with the same stimulus, observers could be asked if there were two digits (yes response) or five (no response) and so forth.

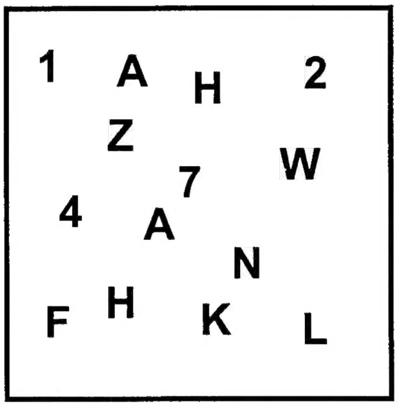


Fig. 5 - Multiple target search

In this way, it is possible to estimate the time required to find the first, second, third, and fourth digits. Standard models make different predictions from what we can call our "amnesic" model. In the standard model of search *without* replacement, the number of unchecked distractors declines during the course of search as does the number of undiscovered targets. The result is a linear increase in the time required to find successive targets.

In the amnesic model of search *with* replacement, as search progresses, the number of available targets drops while the number of potential distractors remains the same. As a

consequence, the time required to find N targets will be an accelerating function of the number of targets to be found. Sample results are shown in Figure Six: The most instructive data are those for displays with five digits present. These data show the clear acceleration predicted by the amnesic model. Overall, the data reject the standard memory model and are consistent with the amnesic model. It is important to note that the memory model that is rejected is a model that proposes a *perfect* memory for all rejected distractors. It is harder to reject a less comprehensive memory (e.g. memory for the last rejected item or two). Indeed, it is hard to know how search could proceed with absolutely no memory. With no memory, it would seem that the visual system could get "stuck", perseverating on a single salient item.

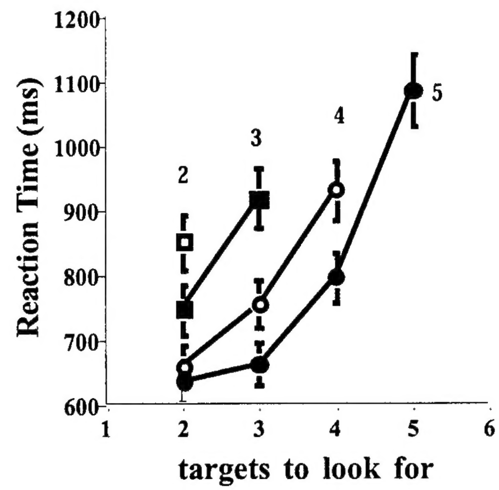


Fig. 6: Results for multiple target search. Parameter on curve is the number of targets present in the display. X-axis shows number of targets observers searched for.

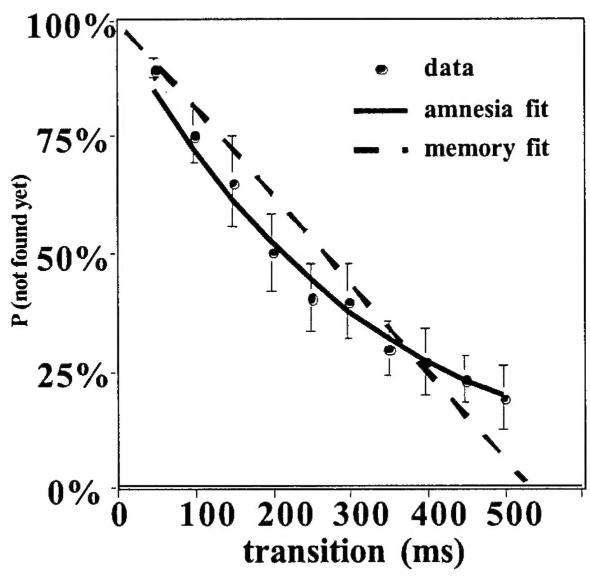


Figure 7 - Results of the third line of research on memory in visual search.

Project 1.3 - A third approach

In a third effort to address the issue of memory in visual search, we had

observers search for a mirror-reversed S or P among standard letters. A target was present on every trial. The displays were entirely static but all of the letters changed color at some point during the trial. The task of the observer was to name the color of the target when it was first seen. In this way, we could determine if the target was found before or after the color change. The measure of interest is the percentage of targets not found prior to the change as a function of variation in the time of change. In a standard memory model, attention marches through the items, one after the other. If there are 10 items, it will take 10 steps to search through the items. There is a 10% chance of finding the target on each step. Consequently, a linear function relates the probability of having not found the target to the moment of color transition. The slope of that function is a measure of the rate of processing. If there is no memory for rejected distractors, then each deployment of attention is independent. If there are N items in the display, the probability not finding the item on the first try is $1-(1/N)$ and the probability after the Jth try is $(1-(1/N))^J$ - an exponential decay. Again, the standard memory model and the amnesic model make qualitatively different predictions about the shape of the data. The results are shown in Figure 7 and are fit better with an amnesic model than with a standard memory model. Again, we cannot reject a model that proposes a small amount of memory.

Assessing parallel models.

It is much harder to generate precise predictions for models that propose parallel processing of multiple letters. However, we can describe the constraints on any parallel model that hopes to explain these data. First, the dynamic search tasks seem to falsify the class of parallel models that relies on steady accumulation of information at multiple loci.

Accumulation is not possible in these tasks. Nevertheless, search is not only possible, but reasonably efficient. One could propose that parallel processing consists of a set of parallel "snapshots" (e.g. one per fixation or, in dynamic search, one per frame). These would be independent of each other. There would be some probability of finding the target with each of these snapshots. In effect, this would be an amnesic parallel model and is probably indistinguishable from the amnesic serial model in its predictions about these experiments. In our discussion of Project Three, we briefly sketch a related argument about the futility of distinguishing serial and parallel models of search.

The important conclusion from this line of work is that, however search is accomplished, it does not appear to involve extensive memory for the course of the search. We can speculate about why this should be the case as it initially appears somewhat counter-intuitive. It seems most likely that this is an example of a type of speed accuracy tradeoff. Maintaining a memory for distractor location probably carries a cost in required time and/or processing capacity that makes it more efficient to search at random with replacement than to search in a more orderly manner, without replacement. The next section describes a different line of experiments that also point to the advantages of fast, sloppy processing over slower controlled processing.

Publications & Manuscripts associated with Project One *(papers marked with an * are included with this report)*

*Horowitz, T. S. and J. M. Wolfe (1998). "Visual search has no memory." Nature **394**(Aug 6): 575-577.

*Horowitz, T. S. and J. M. Wolfe (2000). "Search for multiple targets: Remember the targets, forget the search." Perception and Psychophysics **accepted 6/00**.

This project will give rise to at least two more manuscripts in the next year.

Published abstracts:

Alvarez, G., T. S. Horowitz1, et al. (1999). "New evidence against global accumulation of information in visual search." Investigative Opthalmology and Visual Science **40**(4).

Alvarez, G., T. S. Horowitz, et al. (1999). "Visual search is globally amnesic." paper presented at EPA annual meeting. **March, 1999**: Providence, RI.

Horowitz, T. S. and J. M. Wolfe (1997). "Is visual search lost in space?" Investigative Ophthalmology and Visual Science **38**(4): S688.

Horowitz, T. S. and J. M. Wolfe (1998). "Temporal transients disrupt attentional guidance but not visual search." Investigative Ophthalmology and Visual Science **39**(4): S225.

Horowitz, T. S. and J. M. Wolfe (1999). "Defending the proposition that visual search has no memory." paper presented at EPA annual meeting. **March, 1999**: Providence, RI.

Horowitz, T. S., J. M. Wolfe, et al. (1999). "Amnesic search is not an artifact of stimulus duration." 3rd annual Vision Research conference. **Preattentive and Attentive Mechanisms in Vision**(7-8 May): Ft. Lauderdale, FL.

Wolfe, J. M., T. S. Horowitz, et al. (2000). "Further evidence for amnesic search: Attention is still lost in space." Investigative Opthalmology and Visual Science **41**(4): S760 (Abstract 4033).

Horowitz, T. S., Wolfe, J. M. (1998). Indirect estimates of attentional dwell time. *Proceedings of the Eastern Psychological Association*; **69**.

Horowitz, T. S. & Wolfe, J. M. (1997). Visual search in the eternal present. *Abstracts of the Psychonomic Society*, **2**.

PROJECT TWO: Commanded Search

If visual search processes are truly (or nearly) amnesic, why don't observers use some sort of systematic strategy when searching. Subjects could "read" a display from top-left to bottom-right or attention could spiral out from fixation. Any path would serve the function of memory without the requirement to remember more than the current

deployment of attention and the planned route of deployment. We know that observers do not normally use strategic plans of this sort because, if they did, then there would have been a difference between Static and Dynamic search slopes in the Section 1.1 above. There is order when observers search more complex images for longer periods of time (Noton and Stark 1971; Zangemeister, Sherman et al. 1995) but, except for a bias toward the fovea (Carrasco, Evert et al. 1995; Wolfe, O'Neill et al. 1998), little evidence for order in the deployment of covert attention in standard laboratory search tasks.

Project 2.1 Dynamic Displays

In an effort to understand this, we developed tasks that force observers to deploy attention in a pre-ordained, systematic manner. Sample stimuli are shown in Figure 8. In

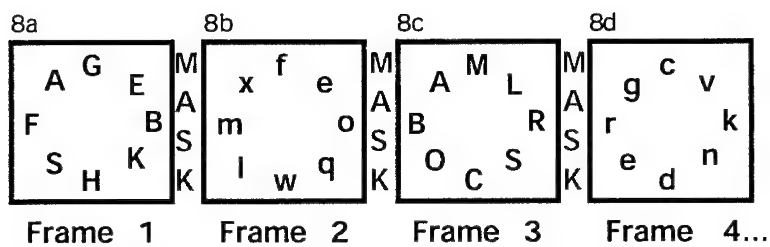


Figure 8: In this Commanded search task, observers move attenion in a clockwise manner from frame to frame. If they move at the correct rate, attention is deployed to the correct item when a target "Y" or "N" appears. In this case, the target is in position 4 on frame 4 (8d).

our Command condition, 12 observers saw 8 frames like Fig 8a-d for 53 msec each followed by a variable duration mask. One target, a "Y" or "N" was present on each trial. This target could only appear at Position One (12 O'clock) on Frame One, Position Two on Frame Two, etc. If an observer deployed attention at the correct rate, clockwise around the circle, attention would be on the target when it appeared (Position 4 - Fig 8d) and they could determine if it was a Y or N. Otherwise, the task was impossible.

Observers were fully informed and trained to move attention clockwise in time to a spatially uninformative tone. A staircase procedure was used to measure the maximum speed that permitted 70% correct performance. Due to software limits, the maximum rate possible was 80 msec/frame in this version of the experiment.

For comparison, observers performed a Random Anarchy condition. Here, the Y or N was present on all frames but moved amongst three locations (different on each trial) between frames. Subjects' deployment of attention was not constrained; they could sample the display at random. Randomization thwarted any parallel accumulation of information and prevented observers from attending to a single location and waiting for the target to arrive. Observers were asked to fixate. Letters were large enough to read without fixation and, critically, the stimulus configuration was the same in Random Anarchy and Command conditions. Any eye movement or other perceptual limitations in the Command condition would also apply to Random Anarchy.

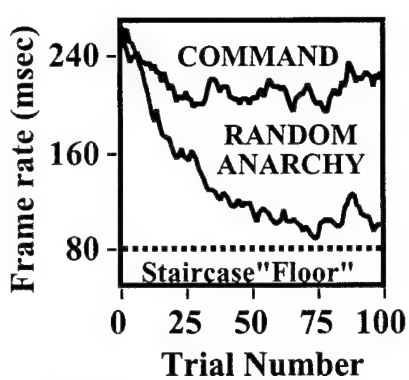


Figure 9: Anarchic search is faster than Commanded search

A control experiment with static letters confirmed that these stimuli are searched at a standard 41 msec/item in normal visual search. Results of the staircase method for the Command and Random Anarchy conditions are shown in Figure 9. The average minimum Commanded rate was 217 msec/frame. This corresponds to a rate of 217 msec/item. The Random Anarchy staircase tended to run into the 80

msec/frame "floor" and produced an average105 msec/frame rate. This would yield an estimate of 105-187 msec/item, depending on assumptions about memory in visual search. This estimate is conservative because of the problems with the 80 msec/frame limit. Other Anarchy conditions without this constraint yielded estimates between 13 and 44 msec/item for Anarchy. We have repeated the Command condition with slight variations in the method. The results are always comparable. Commanded search is much slower than anarchic search. We conclude that observers search unsystematically in standard, laboratory search tasks because the rate of unsystematic search is so much faster than the rate of orderly, commanded search. In this case, anarchy saves time.

Project 2.2 - Static Displays

In order to have converging evidence for the apparently slow rate of Command attention, we have developed a task that compares Commanded and Anarchic search in entirely static displays. Sample stimuli are shown in Figure 10. In the Command condition, the observers task is to start at the 12 O'clock (straight up) position and, moving clockwise, determine the identity of the first mirror-reversed letter (here "S"). In the Anarchy condition, observers simply identify the sole mirror-reversed letter (here "P"). The difficulty with this method is that observers can try to cheat by jumping ahead in the Command condition (and there is some evidence in the data that they did so on some percentage of trials).

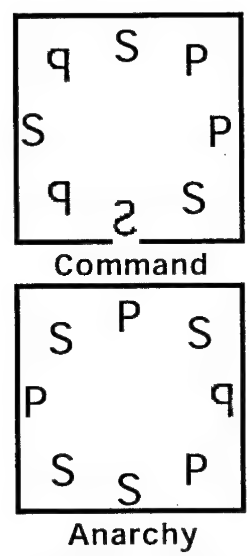


Figure 10: Static displays for measuring Commanded and Anarchic search rates.

Nevertheless, the estimates of the rate of processing are comparable to those obtained with the dynamic displays. Commanded search is much slower than anarchic search.

Projects in this area are ongoing in the lab at the present time.

Publications & Manuscripts associated with Project Two:

*Wolfe, J., G. Alvarez, et al. (2000). "Attention is fast but volition is slow." Nature accepted April, 2000.

A longer paper on this subject will be forthcoming.

Published Abstracts

Wolfe, J. M. and G. A. Alvarez (1999). "Give me liberty or give me more time! Your visual attention is faster if you don't tell it what to do." Investigative Ophthalmology and Visual Science **40**(4): S796.

Horowitz, T. S., A. O. Holcombe, et al. (2000). "Tracking ambiguous motion enables fast attentional shifts." Investigative Opthalmology and Visual Science **41**(4): S422 (Abstract 2234).

PROJECT THREE: Transcending the serial/parallel debate

A great deal of ink has been spilled on debate about the serial vs parallel processing in visual search. There is an interesting issue at stake here. Those of us who argue for a serial model hold that a mandatory serial step in search is a way to deal with the "binding problem" (von der Malsburg 1981; Treisman 1996; Wolfe and Cave 1999). Prior to the arrival of attention, objects appear to be represented as loose bundles of features (Wolfe and Bennett 1997). Attention allows features to be bound to objects in a way that makes explicit the relationships between the features (e.g. Is that a red balloon with green spots or a green balloon with red spots?). Attention to a single object prevents illusory combination of features from different objects (Treisman and Schmidt 1982).

This may or may not be an appealing theoretical argument. In either case, it is not empirical data. It has proven very difficult to produce data that can be used to argue definitively for serial or parallel processing in visual search. One problem is that, for many standard paradigms, the same pattern of results can be obtained with serial and parallel models (Townsend 1990). Recently, we have noted that the dichotomy maybe artificial. The "serial" models, like Feature Integration Theory (Treisman and Gelade 1980; Treisman and Sato 1990) or our Guided Search (Wolfe, Cave et al. 1989; Wolfe 1994) are really hybrid serial/parallel models.

The root of the misunderstanding lies in the interpretation of search slopes. Suppose that a search task produces a target-present slope of 20 msec/item. In serial models, this is taken to mean that one item is being processed every 40 msec, if search has a memory or every 20 msec, if search has no memory (see Project 1). What is usually forgotten is that this slope represents a rate of processing. Processing one item every 20 msec does not mean that it takes only 20 msec to process an item from image to identification. This is implausible. Identification probably takes several hundred msec (depending on the stimulus). A useful analogy is a car wash. We can imagine cars entering a carwash at a rate of 1 per minute. However, this does not mean that it takes one minute to wash the car. It might take five. Several cars can be in the carwash at the same time. Is this a serial process? Certainly the cars are entering one at a time. Is this a parallel process? Certainly cars are being washed in parallel.

In a cognitive carwash it is possible to imagine a car/search item entering the process second and emerging first, but even without such complications, it is clear that such a process will appear parallel if examined with one sort of experimental method and serial if examined with other methods. (For an early version of such a model see Harris, Shaw et al. 1979). Efforts to "falsify" strict serial models are killing "red herrings" because no sensible serial model of search is purely serial. What is needed are specific models that are explicit enough in their architecture to be tested - regardless of their label as "serial" or "parallel".

Publications & Manuscripts associated with Project Three

Wolfe, J. M. (1999). Inattentional amnesia. Fleeting Memories. V. Coltheart. Cambridge, MA, MIT Press: 71-94.

Moore, C. M. and J. M. Wolfe (2000). Getting beyond the serial/parallel debate in visual search: A hybrid approach. The Limits of Attention: Temporal Constraints on Human Information Processing. K. Shapiro. Oxford, Oxford U. Press.

PROJECT FOUR: Guided Search: A modification of the computation of bottom-up salience

Our contribution to the effort to create specific, testable models of visual search is the Guided Search model (Wolfe, Cave et al. 1989; Wolfe 1994; Wolfe and Gancarz 1996). One of the goals of the prior period of grant support was to create the next generation of the model. We are continuing to work on that project which was made more complicated by the discovery that our assumptions about memory in visual search were incorrect.

In brief, Guided Search proposes that serial deployments of attention are guided to likely targets on the basis of parallel processing of information about a limited number of basic features like color, size, and orientation. Thus, if subjects are searching for a T among L's they may search randomly among all items. If they are searching for a red T among red and green L's, they will search randomly though the set of red letters (Egeth, Virzi et al. 1984). Guidance comes in two forms. The preceding example is a case of "top-down" user-driven guidance. Attention is guided toward objects having known features of the target. There is also "bottom-up" activation where attention is attracted to locally salient items (e.g. a green item amongst red).

We have recently proposed a modification of the bottom-up component of Guided Search inspired by a report of Andrew Found that questioned the model (Found 1998). Found looked at the effects of irrelevant feature variation on a conjunction search. The critical conditions for his experiment are shown in Figure 11.

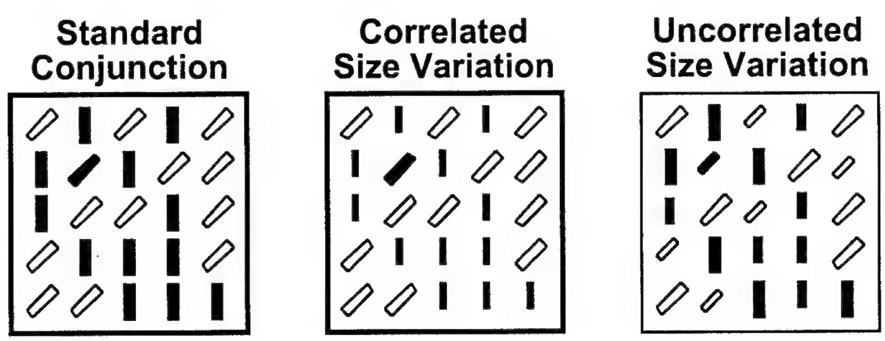


Figure 11: Found (1998) reported that the correlation of an irrelevant feature with relevant features improved the efficiency of a conjuntion search. This was not predicted by published version of Guided Search.

The first panel shows a standard conjunction search for a black tilted item among white tilted and black vertical distractors. Found's innovation was to introduce variation in an irrelevant feature (here size). In the Correlated condition, vertical black items are all

small and tilted white items are all big. The target, when present, could be either big or small. Size information was irrelevant but correlated with the relevant color and orientation information. In the Uncorrelated condition, the size variation was unrelated to the orientation and color variation.

Published versions of Guided Search clearly predict that the correlation of an irrelevant feature should not influence search efficiency. No top-down guidance by size is possible. There would be bottom-up activation associated with the size variation. It would be noise and should reduce search efficiency. However, its impact should be the same in Correlated and Uncorrelated conditions because, in published Guided Search, featureal dimensions are modular and the pattern of activity in one dimension should not have an impact on another dimension.

Contrary to this prediction, however, Found reported that the Correlated condition was more efficient than the Uncorrelated. The effect was small but reliable and we have replicated it. This makes some intuitive sense if one notices that the Uncorrelated condition of Figure 11 looks more "noisy" than the correlated case. Found proposed that this required "parallel processing of conjunctions". However, we have been able to model the result without giving up any of the core assumptions of Guided Search. A cartoon of the published version of the bottom-up component of Guided Search is shown in Figure 12. For each dimension, local differences between an item and all of its neighbors are summed *within* a featureal dimension and then a weighted sum across dimensions produces the overall activation.

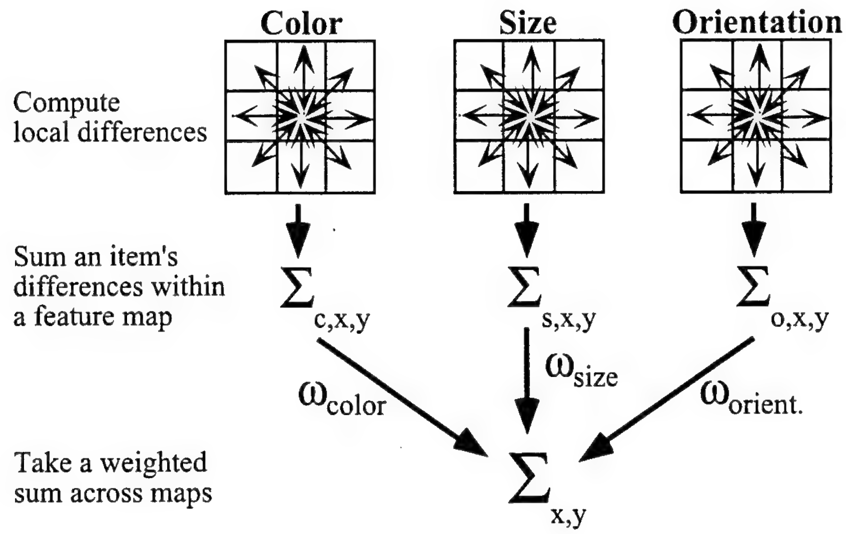


Figure 12: Calculation of bottom-up activation in published Guided Search. Local differences are computed between an item and all neighbors. This is done separately for each featural dimension. The differences are summed within each feature map creating a "color" activation, a "size" activation and so on for each item. The final, bottom-up activation for an item is the weighted sum of the individual feature activations.

The required change in Guided Search is shown in Figure 13. It has two parts. First, local differences are summed *across* featureal dimensions for each pair of items before summing all of these local differences into a single activation for a specific item. Second, the local differences pass through a compressive non-linearity before being summed into a bottom-up activation for a specific item. This may sound more arbitrary than it is. This non-linearity simply captures the fact that the perceptual, attention-grabbing difference between two items reaches a maximum. As an example, the salience of the difference between a red vertical item and a green horizontal item would not be that much greater than the salience of the difference between a red vertical item and a green vertical item.

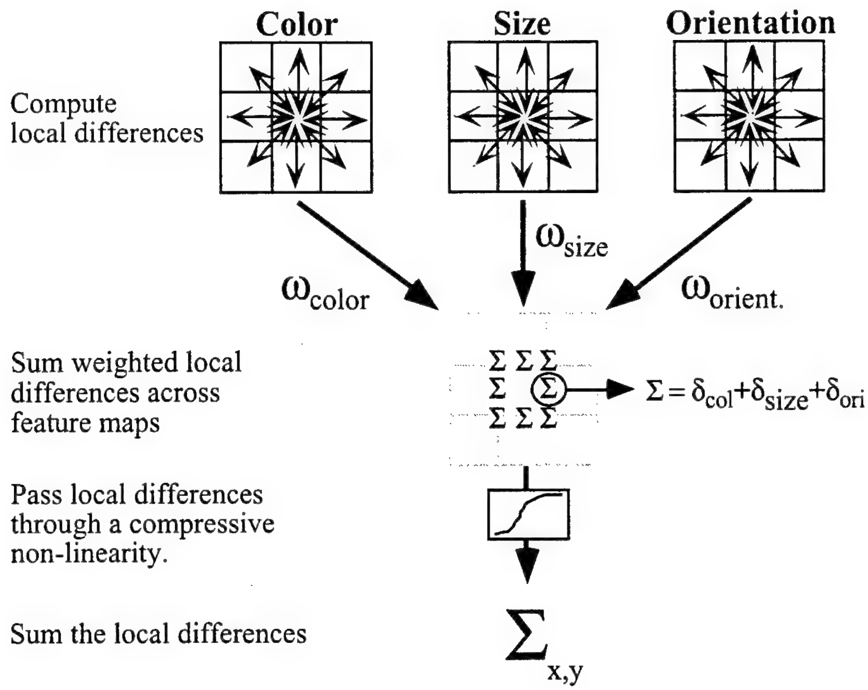


Figure 13: Modified calculation of bottom-up activation: Local differences are computed for each featural dimension. These are summed locally and then passed through a compressive non-linearity. These local differences are then summed to create the bottom-up activation for an item

We have implemented a partial Guided Search model with this modification. Sample results are shown in Figure 14. The basic pattern of results from our replication of

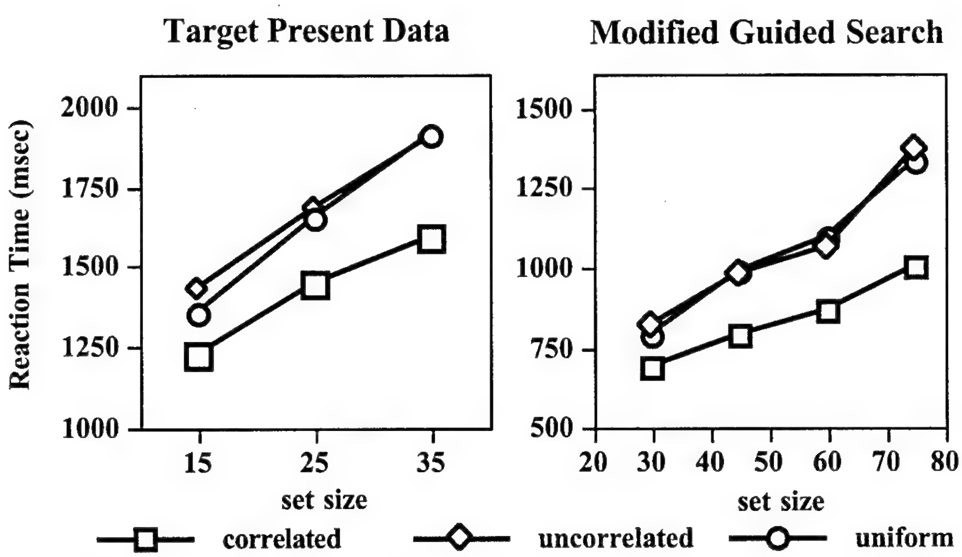


Figure 14: A simulation of the modified Guided Search model captures the basic pattern of the actual data.

Found's experiment is captured by the simulation. The model continues to successfully simulate other basic search results using the same set of parameters that produce the results in Figure 14. We are currently working to expand this partial model into a new, full Guided Search model, which will also incorporate our findings from Project 1 concerning memory in visual search.

Publications and abtracts related to Project Four

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PROJECT FIVE: Visual Search and Optic Flow

In visual search, items defined by a unique feature are found easily and efficiently. Search for a moving target among stationary distractors is one such efficient search. Search for a stationary target among moving distractors is markedly more difficult. This basic search asymmetry lacked clear documentation in the literature. We have now provided that evidence. We tested three types of motion: linear, in which all distractors moved the same way; random linear, in which distractors moved in straight lines but in random directions; and "Brownian" motion, in which each item moved on its own random walk. For each type of motion, we had subjects search for a "dead" stationary target among "live" moving distractors, or vice versa. Results are shown in Table One:

	Linear Motion		Random Linear Motion		Brownian Motion	
	Live	**Dead**	**Live**	**Dead**	**Live**	**Dead**
Present	-1.2	5.0	-1.2	12.9	-1.5	14.0
Absent	-1.3	9.5	-0.6	24.6	-0.2	16.5

Table One: Slopes in msec/item for six motion search tasks. Note that search for a "live" item is always very efficient and always more efficient than the companion search for a "dead" item.

With those results as a baseline, we went on to ask about search for a moving target with simulated observer motion. Consider that much visual search in the real world is carried out by moving observers. Except for items that are moving along the line of sight or that are moving with the observer, this means that all items in the field will move on the retina. We asked if the visual system can discount this 'optic flow' (Gibson 1950). We compared cases where a field of dots moved in a manner that was consistent with observer motion to cases where the dots had the same individual motions but were spatially rearranged in order to make the overall motion inconsistent with observer motion. We found that the only factor that was important was local motion contrast. If the target was moving in manner that made it locally distinctive, it was found efficiently. Otherwise, search was inefficient. There was no evidence of a privileged status for optic flow stimuli.

Manuscripts and Abstracts Related to Project Five

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